Neural Computation

NEUR416 / CAAM416 / ELEC 489/589

Rice University
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Prof. Xaq Pitkow
xaq@rice.edu

How does the brain work? In this course you will learn mathematical theories of computation by the brain to answer:

What does the brain compute?	(representations, latent variables)
How does it compute?	(nonlinear transformations and dynamics)
Why does it compute that way?	(inference, efficiency)

We will apply these theories to challenges in sensory perception, learning and memory, cognition, and behavior. You'll develop skills through problem sets using mathematics and computer programming.

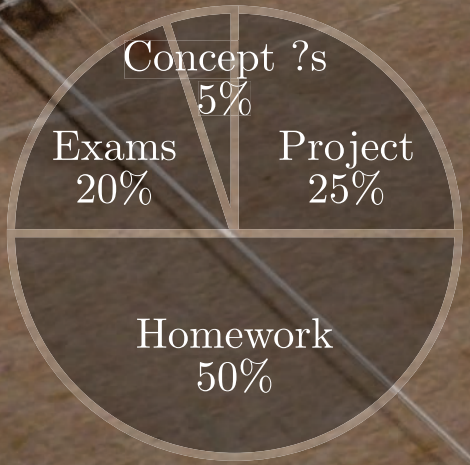
Prerequisites:

- Multivariate calculus
- Linear algebra
- Probability / statistics
- Computer programming

Recommended Book: *Theoretical Neuroscience* by Dayan and Abbott

Class format: interactive lecture TTh 2:30–3:45, Duncan Hall 1046
Homeworks will be about half math, half programming.

Grading



Neural Computation

NEUR 416 / CAAM 416 / ELEC 489 / ELEC 589

1. Course Summary

How does the brain work? Understanding the brain requires sophisticated theories to make sense of the collective actions of billions of neurons and trillions of synapses. Word theories are not enough; we need mathematical theories. The goal of this course is to provide an introduction to the mathematical theories of learning and computation by neural systems. These theories use concepts from dynamical systems (attractors, chaos) and concepts from statistics (information, uncertainty, inference) to relate the dynamics and function of neural networks. We will apply these theories to sensory computation, learning and memory, and motor control. Our learning objectives are for you to formalize and mathematically answer questions about neural computations including "what does a network compute?", "how does it compute?", and "why does it compute that way?"

2. Instructors:

Xaq Pitkow, Baylor College of Medicine & Rice University; xaq@rice.edu. Duncan Hall 2046.
Yicheng Fei, Lokesh Boominathan (Teaching Assistants); yf17@rice.edu, lb36@rice.edu.
Office hours to be determined.

3. Course Description

Tuesdays and Thursdays, 2:30-3:45 pm
Location: Duncan Hall, DH 1046, Rice University
Recommended textbook: *Theoretical Neuroscience*, by Dayan and Abbott

Audience: Graduate and undergraduate students with quantitative training and interests in theories of how the brain works.
Prerequisites: calculus, linear algebra, probability and statistics, some programming experience
3 credits, Elective

4. Grading Criteria: homework (50%), quizzes (5%), two exams (10% each), and final project (25%).

Homeworks turned in late (after 11:59pm) without pre-approved justification will lose 5% per day.

Several short quizzes (**Concept Questions**) must be completed before class, to get us started thinking about certain ideas. These do not require mathematical computation but rather emphasize conceptual reasoning.

Exams: 3-hour take-home exams. You may use your notes, lecture notes, and readings, but no internet.

Final projects will have a 15-minute in-class presentation (50%) and a written report (50%, ~6–10 pages). The topic of your final projects is flexible. Examples include:

- Reproducing and slightly extending results in a theory or modeling paper
- Analyzing real or simulated data in context of a theory
- Quantitatively contrasting or critiquing competing theories
- Interactive visualization of an interesting theoretical concept
- Historical review of a core theoretical idea

Undergraduates may work in pairs if desired. Individual contributions should be documented. Graduate students taking ELEC 589 are expected to work alone on projects, and to have more comprehensive results (~10 pages for grads, versus ~6 pages for undergrads).

Date	Content	Reading (DA = Dayan and Abbott)	Homework
11jan	Introduction Goals of neural computation		HW1: fun with gaussians and information (due 17jan)
13jan	Efficient coding 1		
18jan	Efficient coding 2	DA 4.1–4.2, appendix on Fourier Transforms van Hateren 1992	HW2: efficient coding (due 24jan)
20jan	Population codes: *encoding* (tuning curves, receptive fields)	DA 1.1–1.3 DA 3.1–3.3	HW3: population codes (due 31jan)
25jan	*decoding* (estimation, discrimination, action)		
27jan	Feedforward networks (1 layer, perceptrons)	DiCarlo and Cox 2007	HW4: feedforward nets (due 8feb)
1feb	Learning in networks: perceptron learning rule, Hebbian plasticity, backpropagation	DA 8.1–8.2, 8.4	
3feb	Multilayer nonlinear feedforward networks: *recoding* Object recognition by deep networks	Bishop 9.2	
4feb (FRI)	Theoretical and Computational Neuroscience Symposium location = zoom *gulfcoastconsortia.org/events/16th-annual-gcc-conference-on-theoretical-and-computational-neuroscience-february-1-2019/*		
8feb	Linear recurrent networks (deterministic)	DA 7.4, up to linear recurrent networks. Appendix: Linear Algebra, Differential equations	HW5: linear recurrent networks (due 22feb)
10feb	SPRING RECESS		
15feb	Univariate stochastic linear dynamics	Scholarpedia: Stochastic dynamical systems	
17feb	Multivariate stochastic linear recurrent networks Kalman filter, line attractors, integrators	How a Kalman Filter works, in pictures. Gold and Shadlen 2001	
	Exam 1 covers up to here! (due 3mar)		
22feb	Nonlinear dynamics I: overview	Strogatz Ch 1	HW6: nonlinear dynamics (due 28feb)
24feb	Nonlinear dynamics II: Winner-take-all, Cooperative networks	Wilson and Cowen 1972 DA 7.4 from Nonlinear recurrent networks, DA 7.5	
1mar	Balanced networks	DA 7.5, 10.1–10.2	Project preparation
3mar	Project check-in		
8mar	Associative memory: Hopfield network (discrete attractor)	DA 7.4: Associative Memory. Hopfield 1982	HW7: Hopfield net (due 11mar)
10mar	Boltzmann machine (probabilistic computation, unsupervised learning)	DA 7.6; 8.4: "contrastive Hebbian learning" Ackley 1983	HW8: Boltzmann machine (due 25mar)
	SPRING BREAK		
22mar	Probabilistic population codes	Ma et al 2006 Berkes et al 2007	Project preparation
24mar	Causal inference Context dependent computation, gating	Bishop 8.2–8.3 Mante et al 2012	

	Exam 2 covers up to here! (due 28apr)		
29mar	Motor control	Shenoy et al 2013	
31mar	Reinforcement learning	DA 9	
5apr	Microcircuitry, macrocircuitry, evolution, and inductive biases	Cisek: Resynthesizing behavior through phylogenetic refinement	
7apr	The Free Will Theorem	The Strong Free Will Theorem	
12apr	overflow		
14apr	Project presentations		
19apr	Project presentations		
21apr	Project presentations		Written projects (due 25 apr)